

# MODELLING SPATIAL AND TEMPORAL CHANGES IN LAND USE/COVER OF MARMARA ISLAND (TÜRKİYE) USING CA-MARKOV MODEL

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## Highlights:


- CA-Markov projects 46% mining expansion on Marmara Island by 2055;
- NDVI reveals major vegetation decline near active mining areas;
- NDVI-CA-Markov integration links LULC transitions with ecology;
- balanced planning is vital for resilient and sustainable land use.

## Article History:

- received 04 April 2025
- accepted 17 December 2025

**Abstract.** In this study, Geographical Information Systems and Remote Sensing techniques were used to analyse the temporal spatial dynamics of land use on Marmara Island for 1991, 2001, 2011, and 2023 years representing major socio-economic transitions in Türkiye and to model future land use for 2055 using the CA-Markov approach. NDVI values derived from multi-temporal Landsat imagery were used to assess vegetation responses to LULC change. Results indicate substantial declines in forests (38.4%), grasslands (28.3%), shrublands (54%), olive groves (15.4%) and agricultural areas (56.4%) between 1991 and 2023, while mining areas increased by 52% and are projected to expand by an additional 46% by 2055. NDVI values (−0.26 to +0.69) show pronounced vegetation loss in northern mining zones and relatively stable agricultural-forest mosaics in the south. Overall, the findings demonstrate that mining driven anthropogenic pressures are reshaping the island's ecological structure, underscoring the need for sustainable land management.

**Keywords:** land use change, CA-Markov model, remote sensing, NDVI, mining areas, landscape planning.

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## 1. Introduction

Land use, climate, and socio-economic changes interact in ways that influence the resilience and sustainability of social-ecological systems (Atik et al., 2010; Mcgarigal et al., 2018; Kariuki et al., 2022; Bingöl et al., 2023; Vohra & Tiwari, 2023; Thakur et al., 2021). When analysed on a global scale, 12 million hectares of agricultural land are lost every year in rural areas. Urban land areas, on the other hand, increased by 346.4 thousand km<sup>2</sup> between 1992 and 2016 and grew by 1.3% (He et al., 2019). Especially when the projections of population density change are analysed, it is estimated that land cover in cities will increase by 1.2 million km<sup>2</sup> by 2030 (Seto et al., 2012; Khwarahm et al., 2021; Altiner, 2022).

Mining operations have a important impact on land use/land cover (LULC) change. At the same time, these studies reveal different scope and content of impacts on urban and rural areas (Uzun & Bollukcu, 2009; Kalaycı & Uzun, 2017; Köse & Kul, 2020; Gulpinar Sekban & Acar, 2021). Mining activities cause certain changes in the

structure of ecology. In particular, it reveals many effects such as change in soil quality, destruction of vegetation, water pollution, damage to wildlife, and negative effects on visual landscape (Emir & Yıldırım, 2024). In order to minimise these effects, to restore the ecological balance in mining areas and to eliminate other losses, recovery works are carried out in many places. Countries that produce the most in mining are generally characterised by their natural resources, mining infrastructure and technological capacities. When the share (%) of mining production and gross national production is analysed, these countries are China 23.6%, Australia 8.6%, Russia 7.3%, USA 7.2% and Canada 5%. The share of Turkey's mining sector in gross national production is 1.2% (Istanbul Mineral Exporters Association, 2024).

When the environmental impacts and economic significance of mining activities are considered together, it becomes evident that the sector must be addressed not only from a production-oriented perspective but also through the lenses of spatial planning, environmental management, and sustainable development (Rentier &

Cammeraat, 2022; Dikgwatlhe & Mulenga, 2023). In addition to the technical assessment of land use and mining impacts, the inclusion of stakeholder perspectives is essential for effective and sustainable planning. Policy makers play a crucial role in regulating mining operations and ensuring compliance with environmental protection standards. Conservation groups contribute by monitoring ecological integrity, promoting biodiversity conservation, and advocating for land restoration strategies in post-mining areas. Likewise, tourism authorities emphasize the preservation of natural and cultural landscapes, which are often adversely affected by mining expansion. Integrating the insights of these stakeholders into spatial planning processes enhances decision-making, promotes transparency, and supports the development of land use policies that balance economic growth with environmental sustainability and community well-being (Keenan & Holcombe, 2021; Hou et al., 2021; Mhlongo, 2023).

Examining the temporal variations in existing land uses, mining activities, and other environmental and socio-economic factors influencing these changes is crucial for understanding landscape dynamics and developing future LULC models in the planning of sustainable urban and rural areas (Soltanmohammadi et al., 2010; Mohan et al., 2011; Dale & Kline, 2013; Ghosh et al., 2017; Zhou et al., 2018; Cao et al., 2023; Sakizadeh et al., 2023). In this context, numerous studies have successfully employed spatial modelling approaches such as Cellular Automata (CA), Markov chains, SLEUTH, and CLUE-S to predict future land-use dynamics (Verburg & Overmars, 2009; Sang et al., 2011). Among these, the CA-Markov model has gained prominence for its ability to simulate complex spatial processes by combining the stochastic transition probabilities of Markov chains with the spatial dependency and neighborhood effects of cellular automata (Hu et al., 2013; Zheng & Hu, 2018). Compared with data-intensive models like CLUE-S or purely statistical machine-learning approaches, CA-Markov offers a parsimonious, transparent, and data-efficient structure, making it particularly suitable for areas with limited socio-economic datasets and pronounced spatial constraints such as islands and coastal territories (Khunrattanasiri, 2020).

CA-Markov model is a tool used in situations where it is difficult to define the processes and changes of the landscape, and it works on modelling predictions for the future situation by examining the changes from the past and present (Altiner, 2022). Although the evaluation of the accuracy of the model is among the most important stages of modelling processes, the 'kappa statistical' test is generally used at this stage (Eşbah et al., 2009; Kumar & Sharma, 2022). The CA-Markov model excels in time series and spatial forecasting, making it highly effective for simulating spatio-temporal land use changes in both quantity and distribution. Therefore, it is the most widely used method for modelling land uses (Hyandye & Martz, 2017; Mansour et al., 2020; Baqa et al., 2021; Chang et al., 2021; Amir Siddique et al., 2021; Ghosh et al., 2021; Daba & You, 2022; Fu et al., 2022; Hussain et al., 2024; Solaimani

& Darvishi, 2024). In addition, the CA-Markov model is an important tool used in spatial and temporal dynamic modelling of LULC changes, as it has the ability to efficiently combine both remote sensing (RS) and geographic information system (GIS) data (Corry, 2005; Alphan et al., 2022). The importance and progress of space sciences, rapid developments in RS and GIS techniques have contributed to the widespread use of CA-Markov model (Chen et al., 2012).

In addition to the analysis of LULC and the simulation of future land use scenarios, examining vegetation dynamics offers a vital perspective for understanding the ecological consequences of mining activities (DeWitt et al., 2017; Mi et al., 2019). Among the various remote sensing approaches, the Normalized Difference Vegetation Index (NDVI) is one of the most reliable and widely used indicators for assessing vegetation greenness, density, and overall ecosystem vitality. Monitoring NDVI trends over time enables the identification of degradation patterns caused by mining, such as vegetation loss, soil exposure, and reduced ecosystem resilience. Furthermore, long-term NDVI monitoring provides valuable insights into seasonal and interannual fluctuations in vegetation productivity, allowing for the detection of subtle environmental changes that may not be captured by conventional land cover classifications (Sahu & Kumawat, 2022; Listyono & Manurung, 2025). By comparing NDVI dynamics with the spatial expansion of mining zones, it becomes possible to quantify the degree of ecological disturbance, assess the recovery potential of abandoned sites, and evaluate the cumulative impacts of mining and urbanization on surrounding ecosystems (Cui et al., 2018; Punia et al., 2021).

In this study, the temporal and spatial changes in the land use/land cover of Marmara Island, which is the second largest island of Turkey and located within the borders of Balıkesir province, in 1991, 2001, 2011 and 2023 were calculated and a predictive land use model for 2055 was created. The main objective of the study is to examine the effect of mining sites on land use classes over time and to examine the relationship with ecosystem resources in the future. RS and GIS were utilised in the calculation of land use changes, and the CA-Markov model was used to create the estimated land use map for 2055. In addition, NDVI was derived from multi-temporal Landsat imagery to monitor vegetation dynamics and assess the ecological impacts of mining expansion on forest and agricultural areas. By integrating NDVI analysis with LULC change detection and future land use projections, the study provides a comprehensive understanding of how mining-driven transformations influence vegetation cover, ecological resilience, and sustainable land management on Marmara Island.

The research focussed on the following questions.

1. To what extent are the temporal and spatial changes in the land use/cover of Marmara Island?
2. Which land use classes have been affected by the mining sites on the island over time and in which direction are the future change trends?

The distinguishing feature and methodological novelty of this study lies in its explicit integration of NDVI-based ecological metrics with spatial land-use transition modelling. Numerous studies have employed NDVI to examine LULC changes; however, approaches that explicitly integrate NDVI-based ecological metrics with spatial land-use transition modelling remain comparatively limited. Addressing this gap, the novelty of the present study lies in the integrated use of CA-Markov spatial modelling and NDVI-derived vegetation metrics to quantify the ecological consequences of human-induced land-use dynamics, with particular emphasis on mining expansion on Marmara Island. Although NDVI does not allow discrimination of vegetation species or community composition, it provides a robust and widely accepted indicator of vegetation greenness and health at landscape scales, which is consistent with the spatial and temporal resolution of the adopted land-use modelling framework. By embedding vegetation condition assessment directly within the land-use transition analysis rather than treating NDVI as a supplementary indicator this research enables a more robust evaluation of spatio-temporal interactions between anthropogenic pressure and ecosystem response. Moreover, the combined use of CA-Markov simulation and NDVI-based vegetation evaluation provides a replicable approach for assessing long-term environmental changes in other mining-affected insular or coastal regions.

## 2. Material and method

### 2.1. Material

In this study, Marmara Island, which is located in the southwest of the Marmara Sea in Türkiye, within the Marmara Archipelago and within the borders of Balıkesir province, was selected as the research area. The island is located geographically 40°38'55" and 40°38'28" Northern latitudes, 27°34'13" and 27°43'19" Eastern meridians. With a surface area of 117 km<sup>2</sup>, Marmara Island is the second largest island in Türkiye and the largest island in the Marmara Archipelago (Figure 1). The semi-humid Marmara

climate prevails on the island (Koç & Gündüz, 2022). In addition, Balıkesir, the province where the island is located, is among the important cities of Türkiye in terms of historical and cultural values.

Although the elevation of Marmara Island, which is exposed to metamorphic and tectonic processes, is generally not high, the highest places are located in the central parts of the island. Figure 2 shows the slope and elevation map of the study area prepared with the help of GIS.

The island consists of three basic geological units: schist, marble and granodiorite composite gneisses. These units are named as Saraylar Complex, Gündoğdu Metamorphites, Erdek Complex, İlyasdağı Metagranodiorite, Marmara Marble and (Aksoy, 1999).

The operation of marble quarries on the island continues from ancient times until today. The origin of the word Marmara comes from the Greek word (marmor) meaning marble and there are 400 million m<sup>3</sup> marble reserves. Marble continues to be mined in the Saraylar town of Marmara Island starting from ancient times, from Roman Byzantine and Ottoman times to the present day. The fact that the island has an economic structure focused on mining, tourism and agriculture causes anthropogenic pressure to increase day by day (Alptekin, 2021; Uzun, 2023).

### 2.2. Method

The methodological stages of the study for calculating the temporal and spatial changes in the LULC of Marmara Island over the years, performing NDVI analysis, and creating the estimated land use model for 2055 are presented in Figure 3. Detailed information about each stage of the method, including the derivation of NDVI values from multi-temporal Landsat imagery and their integration with LULC and CA-Markov analyses, is provided under the related subheadings.

#### 2.2.1. Data sources and processing

Satellite imagery obtained from the United States Geological Survey (USGS) Earth Explorer platform constituted the primary data source for analysing the spatiotemporal

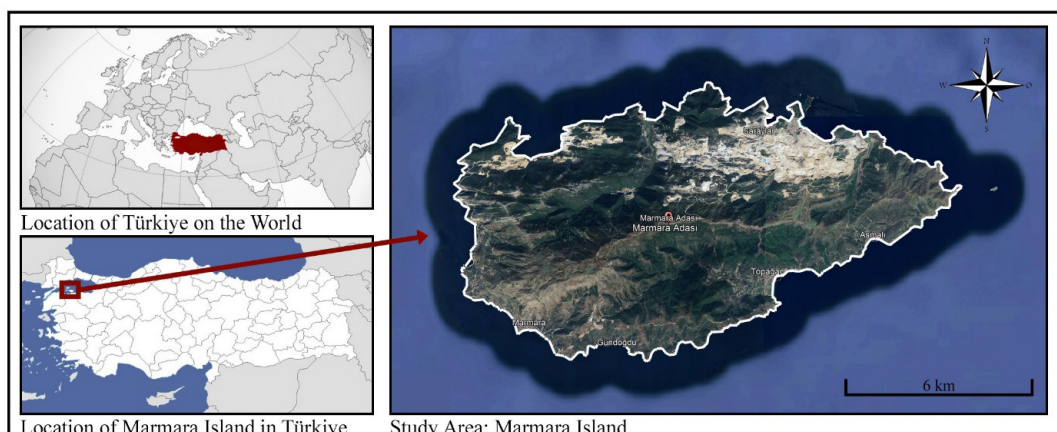
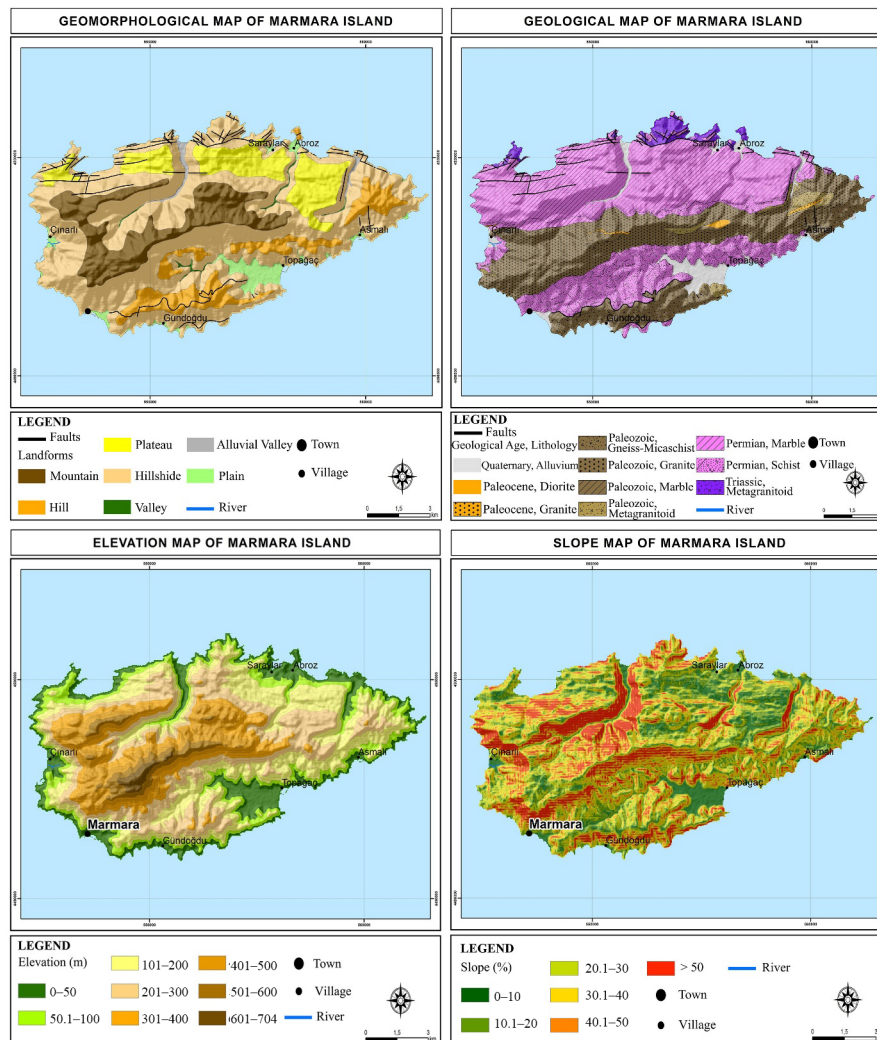


Figure 1. Location of the study area



**Figure 2.** Slope, elevation, geological and geomorphological map of the study area

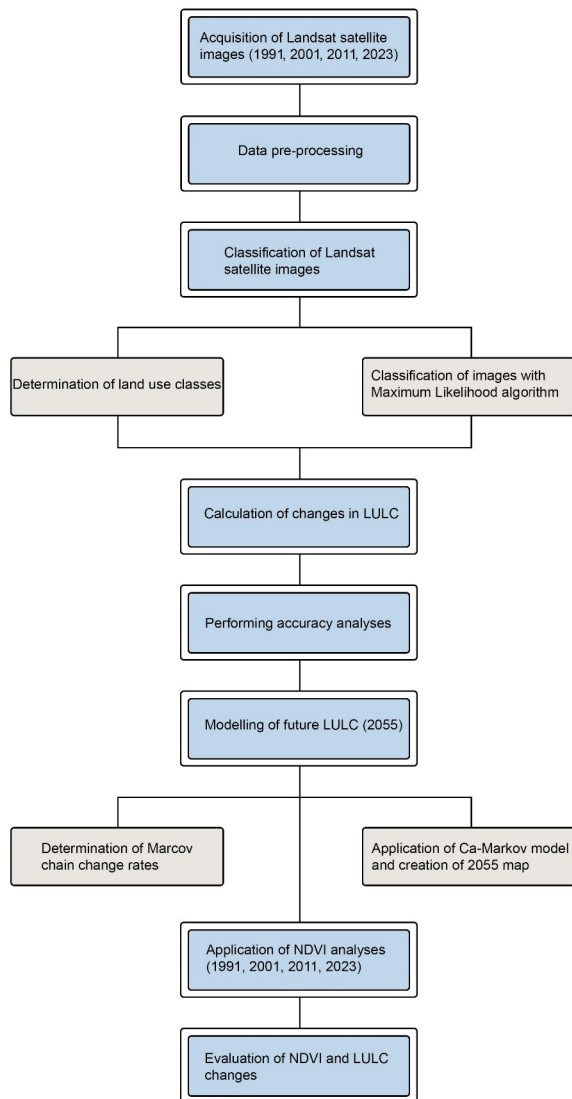
dynamics of LULC on Marmara Island for the years 1991, 2001, 2011, and 2023. These four benchmark years were deliberately selected to represent both decadal intervals and critical socio-economic transition phases in Türkiye that have directly shaped regional land-use patterns.

From a historical perspective, 1991 reflects the early post-industrialisation period, during which mining operations and settlement expansion on the island began to intensify. 2001 corresponds to the nationwide economic crisis, a turning point that influenced land-use decisions, agricultural restructuring, and broader socio-economic shifts. 2011 captures a phase of economic recovery, infrastructural development, and accelerated extractive activities, resulting in substantial pressure on natural landscapes. 2023, the most recent observation year, represents the current period characterised by both heightened industrial activity and emerging sustainability-oriented policy frameworks. The selection of 2023 also aligns with the availability of high-quality, cloud-free Landsat 8 OLI\_TIRS\_L2SP imagery.

All satellite scenes used in the analysis were obtained at a spatial resolution of 30 m, ensuring temporal

comparability across the study period. Prior to analysis, each image underwent essential pre-processing procedures, including radiometric and atmospheric corrections, geometric rectification, and reprojection to the Universal Transverse Mercator (UTM) Zone 35N, WGS 1984 coordinate system. These steps were applied to minimise geometric distortions, enhance spectral consistency, and enable accurate multi-temporal comparison. The technical specifications of the imagery, including satellite missions, sensor types, acquisition dates, and processing levels, are summarised in Table 1.

In this study, NDVI values for the years 1991, 2001, 2011, and 2023 were calculated and spatially mapped to evaluate how long-term LULC transitions have influenced vegetation dynamics on Marmara Island. Multi-temporal, multispectral satellite images derived from the Landsat 4 TM, Landsat 5 TM, and Landsat 8 OLI\_TIRS\_L2SP missions were used as the primary data sources (Table 2). These satellite platforms were selected due to their consistent 30 m spatial resolution, spectral compatibility across sensors, and long-term global acquisition record, which



**Figure 3.** Method flow chart

together enable robust temporal comparison. For NDVI computation, the study employed the red (R) and near-infrared (NIR) spectral bands, which are widely recognized for their sensitivity to photosynthetic activity. Specifically, NDVI was calculated using:

- Landsat 4-5 TM: Red band (Band 3; 0.63–0.69  $\mu\text{m}$ ) and NIR band (Band 4; 0.76–0.90  $\mu\text{m}$ )
- Landsat 8 OLI\_TIRS\_L2SP: Red band (Band 4; 0.64–0.67  $\mu\text{m}$ ) and NIR band (Band 5; 0.85–0.88  $\mu\text{m}$ )

Prior to index generation, all images underwent a standardized pre-processing workflow, including radiometric

calibration, atmospheric correction (LEDAPS/LaSRC), geometric correction, and reprojection to the UTM Zone 35N, WGS-84 coordinate system. These procedures ensured spectral consistency across sensors and minimized temporal and spatial discrepancies.

**Table 2.** Properties of thermal bands used for NDVI

Satellite	Indicator	Band No	Band name
Landsat 4 (TM)	NDVI	3	Red
	NDVI	4	NIR
Landsat 5 (TM)	NDVI	3	Red
	NDVI	4	NIR
Landsat 5 (TM)	NDVI	4	Red
	NDVI	5	NIR
Landsat 8 (OLI-TIRS)	NDVI	4	Red
	NDVI	5	NIR

RS and GIS techniques were employed to generate the slope, elevation, geology, and geomorphology maps of Marmara Island, which constitute essential baseline datasets for analysing the island's physical environment and land-use dynamics. The mapping process integrated multiple data sources to ensure spatial accuracy and thematic consistency. To construct the topographic and terrain-related layers, 1:250,000-scale topography sheets obtained from the General Command of Mapping and General Directorate of M.T.A. were digitised and georeferenced. A high-resolution ASTER Global Digital Elevation Model (ASTER GDEM, 30 m spatial resolution) was used as the primary elevation dataset (NASA Earthdata platform: <https://www.earthdata.nasa.gov/>).

Elevation maps were derived directly from the refined DEM, while slope gradients (in degrees) were computed using a GIS-based slope function that applies a 3×3 neighbourhood algorithm to analyse local elevation variability.

For the geological and geomorphological datasets, 1:250,000-scale geology and geomorphology sheets provided by the General Directorate of Mineral Research and Exploration were used. These analogue maps were digitised, topologically corrected, and harmonised with the coordinate reference system (UTM Zone 35N, WGS-84). Lithological units, fault lines, and geomorphological formations were vectorised and converted into GIS-compatible layers. Geological classes were standardised according to age, lithology, and structural properties, whereas geomorphological units were classified based on relief characteristics, parent material, and process-form relationships.

**Table 1.** Features of satellite images

Satellite	Sensor	Path-row	Acquisition date	Data sources
Landsat 4	TM	180-032	1991/06/16	Landsat 4-5 TM C2 Level-2
Landsat 5	TM	180-032	2001/06/11	Landsat 4-5 TM C2 Level-1
Landsat 5	TM	180-032	2011/05/22	Landsat 4-5 TM C2 Level-1
Landsat 8	OLI_TIRS_L2SP	181-032	2023/07/17	Landsat 8 OLI/TIRS C2 Level-2

All datasets were spatially aligned, resampled where necessary to match the 30 m DEM resolution, and validated through overlay analysis to ensure geometric accuracy. The resulting slope, elevation, geology, and geomorphology maps provide a coherent and comprehensive geospatial framework that supports the interpretation of LULC changes, NDVI dynamics, and mining-induced landscape transformations on Marmara Island.

### 2.2.2. Images pre-processing and classification

Image classification in remote sensing is an important process for analysing land cover changes (Bazi et al., 2021). When scientific researches are examined, image classification is divided into two as pixel and object-based classification (Sarwar et al., 2019). Since the pixel is the most basic unit in satellite images, pixel-based classification method is seen as a traditional classification approach. In this study, the Maximum Likelihood (ML) classifier was selected as the primary pixel-based classification method owing to its strong statistical foundation, long-standing use in RS research, and proven effectiveness in multi-temporal land-cover analyses. The ML algorithm assumes that the spectral responses of training samples for each land-cover class follow a multivariate normal (Gaussian) distribution (Karlis, 2002; Xue et al., 2021). Based on this assumption, the classifier evaluates the probability density function of each pixel across all spectral bands and assigns it to the class with the highest posterior probability (Shivakumar & Rajashekararadhya, 2018; Appala & Sivakumar, 2023; Feyzolahpour, 2024). By incorporating both the mean vector and covariance matrix of each class, ML captures within-class spectral variability and inter-band relationships more effectively than simpler parametric approaches. Compared with alternative pixel-based classification techniques such as Minimum Distance, Spectral Angle Mapper, or Parallelepiped methods, ML has consistently demonstrated superior discrimination performance particularly when representative training samples are available and when spectral separability among classes is moderate to high (Ngandam Mfondoum et al., 2022; Kumar & Garg, 2023). This capacity to model class-specific spectral distributions makes ML especially suitable for heterogeneous landscapes like Marmara Island, where forest, grassland, shrubland, agricultural land, olive groves, settlement areas, and extensive mine quarry sites exhibit distinct, yet sometimes overlapping, spectral signatures.

A further justification for choosing ML lies in the multi-temporal structure of the dataset. The study utilizes Landsat TM, and OLI imagery covering more than three decades. Ensuring methodological consistency across sensors with different radiometric characteristics is essential for reliable temporal comparisons. ML has been widely applied in long-term LULC studies using multi-sensor Landsat archives and has consistently produced stable and comparable outputs, thereby improving the reliability of temporal trend assessments (Foody, 2022; Theres & Selvakumar, 2022). Such continuity was crucial for generating

robust change-detection results for the 1991–2023 period and for ensuring accurate inputs to the subsequent CA-Markov modelling.

In this study, using the ML classifier, LULC maps for Marmara Island were produced for the years 1991, 2001, 2011, and 2023. A total of seven land-cover classes were defined to represent the island's landscape: forest, grassland, shrubland, mine quarry, olive groves, agricultural land, and settlement areas. In this study, the selection of seven land-cover classes was guided by both the CORINE Land Cover (CLC) nomenclature and the ecological patch structure of Marmara Island. The CLC system, widely used across Europe and Türkiye, provides a standardized hierarchical framework that distinguishes major land-cover types and their ecologically meaningful subcategories. Marmara Island's dominant landscape units forests, grasslands, shrublands, agricultural fields, olive groves, mining areas, and settlement zones correspond closely to the CLC Level II categories. Therefore, the classification scheme adopted in this study was derived by adapting the CORINE categories to the island's specific ecological characteristics. This approach ensures that the land-cover classes are both regionally relevant and methodologically consistent with national and European land-cover inventories, thereby enhancing the ecological interpretability, comparability, and long-term monitoring value of the classification results.

The explicit inclusion of mining areas as a separate class is particularly important given the central role of marble extraction in shaping the island's land-cover dynamics. Marmara Island contains extensive mine quarry zones that have expanded significantly in recent decades, affecting vegetation cover, soil surfaces, and overall ecosystem structure. Treating these areas as an independent class enables a more precise quantification of anthropogenic disturbances and allows the ecological implications of mine quarry expansion one of the core objectives of this research to be clearly identified in the classification outputs.

Overall, the integration of the ML algorithm with a seven-class, regionally adapted classification scheme provides a robust methodological framework for accurately characterizing Marmara Island's landscape structure. This approach enhances classification reliability, ensures long-term comparability across multi-sensor datasets, and strengthens the validity of the subsequent CA-Markov modelling and ecological interpretations.

### 2.2.3. Accuracy assessment

In this study, Kappa accuracy analysis was employed to quantitatively assess the reliability of the classified land-cover maps. The Kappa coefficient is widely recognized as an effective statistical measure for evaluating classification performance, as it provides a chance-corrected assessment of agreement between the classified map and reference data. Unlike overall accuracy, which simply reports the proportion of correctly classified pixels, the Kappa statistic incorporates both the diagonal and off-diagonal elements

of the error matrix, thereby offering a more robust indication of classification quality (Visser & de Nijs, 2006; Rau & Shih, 2021; Altiner, 2022).

The Kappa statistic was originally developed by Cohen (1960) to measure inter-observer agreement while controlling for the probability of chance agreement. Its application has since expanded to remote sensing, where it is commonly used to compare the relative performance of different classification algorithms, assess temporal changes in classification accuracy, and evaluate consistency among multi-date LULC maps. By correcting for chance agreement, the Kappa coefficient provides a more nuanced interpretation of classification reliability, making it a preferred metric in accuracy assessment for remotely sensed data (Vergni et al., 2021).

For the accuracy analysis, reference points were created on Landsat satellite images. In addition, 60 points for each class, 420 points for a single year and 1680 points for a total of 4 years were assigned. User and producer accuracies were calculated with the Error Matrix method in ArcMap 10.8 software. The producer accuracy was calculated by comparing the number of correctly classified pixels for each class to the total number of sample pixels for that class. Similarly, user accuracy was determined by dividing the number of correct pixels in each class by the total number of pixels. Overall accuracy was measured as the total number of correct pixels divided by the total number of reference pixels. After determining the overall accuracy, Kappa analysis was performed. Calculation of Kappa coefficient:

$$K = K = \frac{M \sum_{i=1}^r X_{ii} - \sum_{i=1}^r X_{i+} X_{+i}}{M^2 - \sum_{i=1}^r X_{i+} X_{+i}}, \quad (1)$$

where  $K$  – Kappa coefficient;  $r$  – number of rows in the error matrix;  $X_{ii}$  – the  $i$ -th row and  $i$ th column element of the error matrix;  $X_{i+}$  – sum of the  $i$ -th row elements of the error matrix;  $X_{+i}$  – sum of the  $i$ -th column elements of the error matrix;  $M$  – sum of error matrix elements (Cohen, 1968; Çetinkaya & Toz, 2011).

#### 2.2.4. CA-Markov model

In recent years, the integration of Cellular Automata (CA) and Markov Chains (MC) has been the most widely used model (Feng et al., 2011; Cengiz & Yılmaz, 2016). The basic principle of CA is that the space utilisation for any location (cell) can be explained by the current state and changes in neighbouring cells (Tobler, 1970; Han et al., 2009; Yang et al., 2012). First, the concept of Cellular Automata (CA) was formally introduced by John von Neumann in the 1950s, who established the mathematical basis for cell states and local neighbourhood rules, later expanded by Ulam (1962). These early studies laid the groundwork for representing spatial systems through local transition functions, which contemporary CA models express in generalized form as (von Neumann, 1966):

$$S_{t+1} = f(S_t, N). \quad (2)$$

In the given formula  $S$  denotes a set of cellular states. This is the cellular area;  $t$  and  $t+1$  are different moments;  $f$  is the cellular transformation rule of local space (Sang et al., 2011; Fu et al., 2022).

The Markov chain consists of stochastic processes and matrices expressing transformations between land use categories and is often used in modelling, simulation and trend analysis of LULUC (Myint & Wang, 2006; Keshtkar & Voigt, 2016; Rimal et al., 2018). The Markov model is a stochastic model in the time domain and its main objective is to estimate the probability of an event occurring. The state of the event at time  $t$ , transitions to the state at time  $t+1$ , and this new state depends solely on the state at time  $t$  (Markov, 1906; Behera et al., 2012).

$$S_{t+1} = P_{ij} \times S_t. \quad (3)$$

In the formula  $P_{ij}$  is a state transition matrix.

Where  $0 \leq P_{ij} < 1$ , ( $i, j = 1, 2, \dots, n$ )  $P_{ij}$  is the probability that the initial type  $i$  will change to type  $j$ ;  $i$  is the row of the matrix; and  $j$  is the column of the matrix,  $n$  is the number of land use types.

The Markov chain alone is not sufficient to simulate and predict LULC dynamics as it does not consider the spatial distribution or growth direction of each land use class. In order to take into account the geographical and spatial structure of LULC changes, the Markov chain is integrated with the CO model (Subedi et al., 2013; Xu et al., 2022).

In this study, the – CA-Markov model was calibrated using land-use/land-cover data from 1991 and 2023, representing a 32-year historical interval. To maintain temporal consistency between observed and simulated periods, the model projected land-use changes for an equivalent future horizon, extending 32 years beyond 2023 to the year 2055. This symmetrical temporal framework enhances the reliability and comparability of the model's predictive performance.

#### 2.2.5. Application of NDVI analyses (1991, 2001, 2011, 2023)

The NDVI index was originally developed by Rouse (1973) to quantify vegetation vigor using the contrast between red and near-infrared reflectance. NDVI is one of the most extensively used remote sensing indices for assessing vegetation dynamics, ecosystem health, and land cover transformations across spatial and temporal scales (Bhatti et al., 2024; Anwer et al., 2025). NDVI serves as a robust biophysical indicator that quantifies vegetation greenness and photosynthetic activity by utilizing spectral reflectance properties of vegetation canopies (Li et al., 2024; Cai et al., 2025). Due to its simplicity, reliability, and sensitivity to plant physiological conditions, NDVI has become a fundamental tool in monitoring environmental change, land degradation, drought stress, and the impacts of anthropogenic activities on terrestrial ecosystems (Farbo et al.,

2024). It is particularly effective in evaluating vegetation responses to land-use transitions, climatic variations, and disturbances such as mining or urban expansion issues that are of increasing relevance for ecologically sensitive regions like Marmara Island. In this study, NDVI analysis was employed to investigate the spatio-temporal variations in vegetation cover on Marmara Island for the years 1991, 2001, 2011, and 2023.

The index is derived from the distinctive spectral behavior of green vegetation, which strongly absorbs visible red light due to chlorophyll pigments while intensely reflecting near-infrared (NIR) radiation as a result of the internal structure of plant leaves (Ding et al., 2014; Sharma et al., 2015). This spectral contrast forms the basis for distinguishing vegetated from non-vegetated surfaces and allows for quantitative evaluation of vegetation vigor. Mathematically, *NDVI* is expressed as the ratio of the difference to the sum of the *NIR* and red spectral bands, as shown in Equation (4) (Kriegler et al., 1969; Running, 1990):

$$NDVI = \frac{NIR - Red}{NIR + Red} \quad (4)$$

All satellite images were subjected to atmospheric and geometric corrections prior to analysis. NDVI calculations

were performed using ArcGIS 10.8, and annual NDVI raster maps were generated for each study year. The NDVI values range from  $-1$  to  $+1$ , where  $-1$  to  $0$  indicates water bodies,  $0-0.2$  corresponds to bare soil or settlement areas,  $0.2-0.5$  represents sparse vegetation, and  $0.5-1$  denotes dense vegetation cover (Lemenkova & Debeir, 2023; Olufayokemi Rasheedat & Ojodale Samuel, 2025).

The resulting NDVI maps were used to assess the spatio-temporal dynamics of vegetation, identifying patterns of vegetation loss and regeneration across Marmara Island. These changes were further interpreted in relation to the expansion of mining activities and their impacts on the island's ecological structure.

### 3. Results

Satellite images were classified to examine the temporal changes in the land use cover of Marmara Island for the years 1991, 2001, 2011 and 2023. TerrSet 2020 and Arc-GIS 10.8 programmes were used in the application of the CA-Markov method and the classified 1991 and 2023 maps were used to produce the estimated LULC map for 2055. The determination of the Markov Chain change rates and the creation of the CA-Markov 2055 map were carried out

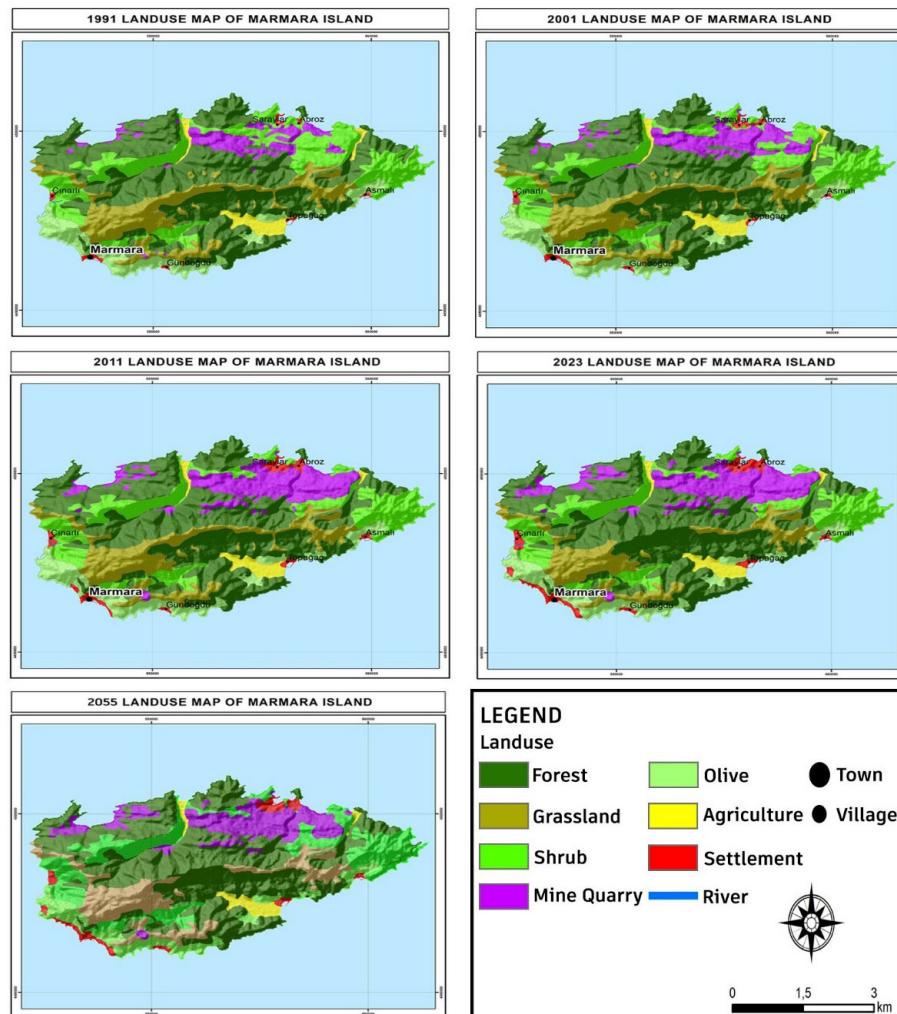


Figure 4. Classified LULC maps (1991, 2001, 2011, 2023) and 2055 estimated LULC map

in TerrSet 2020 programme. The maps of the satellite images of 1991, 2001, 2011 and 2023 classified using the ML algorithm and the estimated land use map of 2055 created by the CA-Markov model method are shown in Figure 4.

In the study, Kappa accuracy analysis was used to analyse the accuracy of controlled classification processes and error matrices were created to evaluate the accuracy of LULC maps. In addition, Kappa accuracy indices for each year were calculated. The overall accuracy rates for the years 1991, 2001, 2011 and 2023 were 89%, 92%, 93% and 93%, respectively, and the Kappa accuracy indices were calculated as 0.88, 0.88, 0.91 and 0.92, respectively.

In order to analyse the results of LULC temporal and spatial changes in Marmara Island, the amount of change was determined numerically. To analyse the LULC changes, post-classification changes were calculated to determine the percentage change and the rate of difference. Land use change amounts and percentage change statistics for the years 1991, 2001, 2011, 2023 and 2055 are shown in Tables 3 and 4.

**Table 3.** The area and changes of LULC classes (hectare)

LULC classes	1991	2001	2011	2023	2055
Forest	1796	1639	1487	1105	957
Grassland	2493	2232	1958	1787	1445
Shrub	1445	919	732	664	480
Mine quarry	4300	5285	5.927	6540	9542
Olive	296	294	258	250	200
Agriculture	195	122	100	85	70
Settlement	919	953	982	1013	1750

**Table 4.** Area statistics of land use types in different periods in Marmara Island (hectare)

LULC classes	Amount of change (ha)			Percentage of change (%)		
	1991–2011	2011–2023	2023–2055	1991–2011	2011–2023	2023–2055
Forest	–309	–382	–148	–17.2	–25.6	–13.4
Grassland	–535	–171	–342	–21.4	–8.7	–19.1
Shrub	–713	–68	–184	–49.3	–9.2	–27.7
Mine quarry	+1627	+613	+3002	+37.8	+10.3	+46
Olive	–38	–8	–50	–12.8	–3.2	–10
Agriculture	–95	–15	–15	–48.7	–15	–17.6
Settlement	+63	+31	+737	+6.8	+3.1	+72.7

When the temporal changes of the land uses of the mining areas of Marmara Island are calculated on the basis of years, there has been an increase of 37.8% between 1991–2011 and an increase of 52% in the 32 years between 1991–2023. According to the research conducted by the Turkish Ministry of Energy and Natural Resources, the number of licensed mines on the island was approximately 15 in 1991, 30 in 2001 and 41 in 2011. In the following years,

this number increased and as of 2023, nearly 100 marble quarries started to operate on the island.

The marble quarries on Marmara Island initially developed in the east-west direction to the south of Saraylar settlement, and then continued to expand from the gulf coasts to the northwest of the island (Uzun, 2023).

Increasing mining activities on the island between 1991 and 2023 have led to certain changes in the structure and functioning of the ecology. Marmara Island has a rich forest vegetation as it is located in the transition area of the Mediterranean climate and the Black Sea climate. Maquis and shrub species from Mediterranean vegetation, Black Sea deciduous trees and coniferous forests coexist on the island. This diversity may vary depending on the island's microclimate, topographical structure and sea influence. However, there has been a 38.4% decrease in the forested areas of the island between 1991 and 2023. In the last 32 years on the island, there has been a decrease not only in forest areas but also in grassland areas by 28.3%, shrub areas by 54%, olive groves by 15.4%, while the decrease in agricultural areas has been the most changed land cover with a rate of 56.4%.

While there has been a decrease in the natural and near natural areas of the island over time, there has been an increase of 9% in the settlement areas. The main reason for the increase in the settlement areas since 1991 has been the improvements in the transport infrastructure and the ease of access to the island. Especially developments in maritime transport have increased access to the island from Istanbul and other coastal cities. With the emergence of urbanisation, the people living in big cities showed interest in quieter places to escape from the noise and stress of the city, which caused them to prefer Marmara Island, and for this reason, the number of summer houses and second residences started to increase on the island. In addition, with the increase in the number of mines, the number of workers working in the mines has also increased and new houses have been built in order to provide employment. Analyses revealed that most of the new settlement areas were olive groves in the previous years. It is seen that the pressure of settlement areas is not only on olive groves but also on agricultural and pasture areas.

The graph of land use change on hectare basis between 1991–2055 and land use conversions map are shown Figure 5 and Figure 6. Land-cover transition map illustrating the spatial changes on Marmara Island from 1991 to 2055. Figure 6 displays pixel-based class conversions between the baseline year (1991) and the CA-Markov projected year (2055). Major transitions include extensive conversions of forest, shrub, and agricultural lands into mining areas, reflecting the long-term expansion of mine quarry activities across the island. Limited ecological recovery is also observed in localized transitions such as mine-quarry to forest or grassland. Additional transitions toward settlement areas and minor shifts among natural vegetation classes highlight the combined effects of mining pressure, land-use intensification, and localized regeneration processes over the study period.

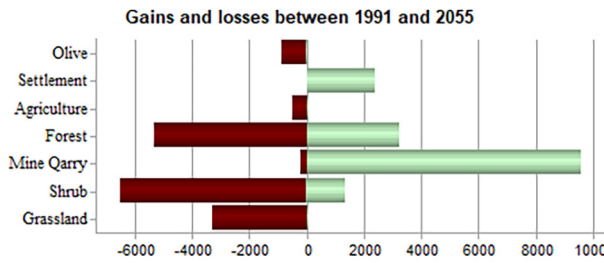


Figure 5. Quantitative changes (in hectares) of LULC classes from 1991 to 2055

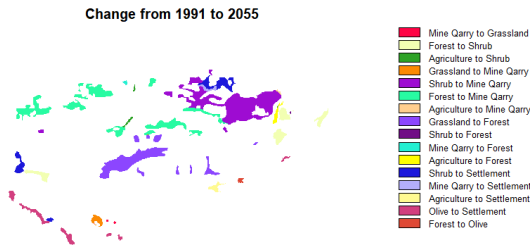


Figure 6. Land use conversions map between 1991–2055

As a result of the creation of the forecast map for 2055 created by the CA-Markov model method and the calculation of land uses, it is predicted that the mining areas will increase by 122% between 1991 and 2055. It is seen that shrub, forest, grassland and agricultural areas will be used respectively for the opening of new mining areas. If another 5242 hectares of land is opened for mining areas between 1991 and 2055, the possibility of negative consequences such as habitat fragmentation, decrease in biodiversity, soil erosion and pollution of water resources, climate change, increase in mining waste, destruction of natural resources and deterioration of soil structure increases.

When the land use and cover changes of Marmara Island between 1991 and 2055 are analysed, it is seen that settlement areas will increase especially in coastal areas and olive groves will decrease in these areas. It is predicted that the increase in settlement in the coastal areas will create a pressure factor on the olive lands here. From past to present, olive groves on Marmara Island have a great ecological, economic, cultural and historical importance. The origin of olive cultivation in Marmara Island dates back to ancient times and has been an important source

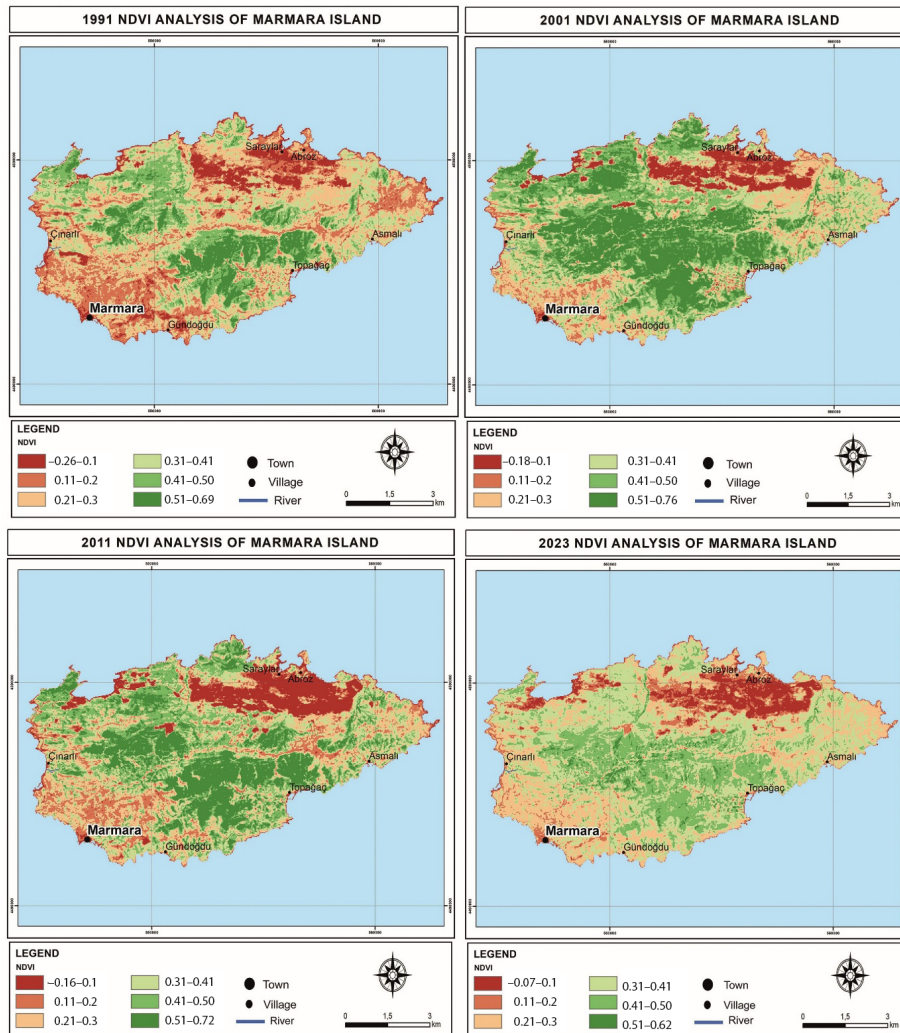


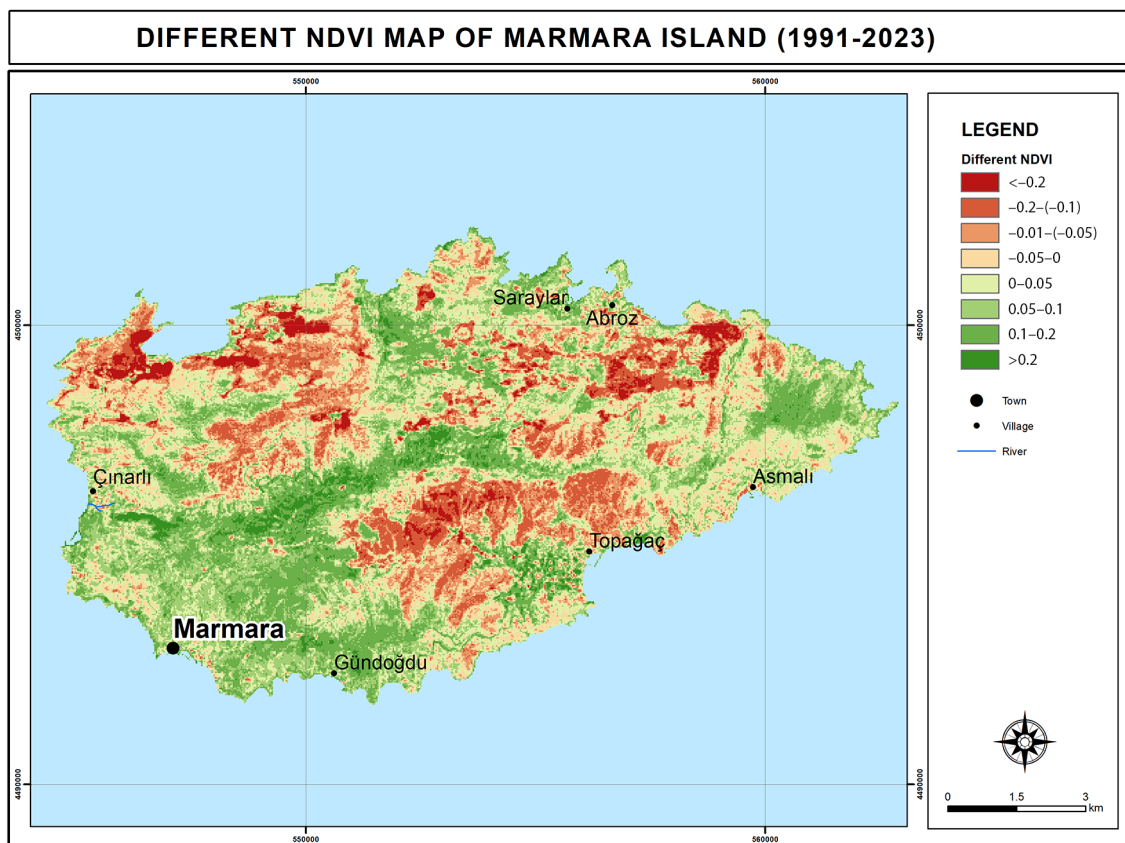
Figure 7. NDVI analysis of the study area for the years 1991, 2001, 2011, 2023

of livelihood for the islanders for centuries. It can be said that this agricultural activity carried out with traditional methods has shaped the social, economic and cultural structure of the island. Olives and olive oil obtained from olive groves on Marmara Island are among the important agricultural products of Turkey. The olive groves on Marmara Island are not only a part of the cultural heritage of the island, but also a social and economic value. However, as a result of the calculations, it is predicted that there will be a 32.4% decrease in olive groves on the island from 1991 to 2055. Between 1991 and 2055, it is expected that there will be a 64% decrease in other agricultural areas other than olive areas. The decrease in planted, dry and irrigated agricultural activities on the island is likely to have negative ecological and economic consequences.

In order to assess the long-term effects of marble quarry expansion on vegetation health and land-surface conditions, the NDVI was utilized as a key indicator to monitor spatiotemporal variations in green cover on Marmara Island. The NDVI approach provides a quantitative framework for detecting ecological degradation and identifying zones of vegetation stress associated with land-use transformations. Within this framework, multi-temporal NDVI maps were generated for Marmara Island for the years 1991, 2001, 2011, and 2023 to analyze the spatial and temporal dynamics of vegetation cover and land-surface conditions (Figure 7). Furthermore, an NDVI difference ( $\Delta$ NDVI) map comparing 1991 and 2023 was derived to quantitatively assess long-term vegetation degradation

and improvement patterns across the island (Figure 8).

NDVI analyses reveal a distinct negative trend across the northern part of Marmara Island particularly around Saraylar, Çınarlı, and Asmalı where NDVI values range between  $-0.26$  and  $+0.10$ . This pattern indicates a considerable decline in vegetation cover driven by long-term marble and limestone quarrying activities, accompanied by surface soil degradation. In contrast, relatively higher NDVI values ( $0.41$ – $0.69$ ) have been preserved in the southern and southwestern zones (Marmara, Gündoğdu, and Topağaç), reflecting the persistence of mixed agricultural and forest mosaics under limited anthropogenic pressure and the protective influence of local topography. The temporal trend further shows a short period of vegetation recovery between 1991 and 2001, followed by a marked decline in 2011 and 2023. This downward shift coincides with the spatial expansion of mining areas, increasing built-up surfaces, and the progressive thinning of forest cover, confirming the direct link between anthropogenic land transformation and vegetation loss. The NDVI difference analysis ( $\Delta$ NDVI), obtained by subtracting 1991 NDVI values from those of 2023, quantitatively identifies zones of vegetation decrease and improvement.  $\Delta$ NDVI values range from below  $-0.20$  to above  $+0.20$ , where negative differences ( $-0.20 < \Delta$ NDVI  $< -0.05$ ) correspond mainly to the northern belt, indicating mining-induced habitat degradation. Conversely, positive  $\Delta$ NDVI values ( $+0.05 < \Delta$ NDVI  $< +0.20$ ) are concentrated in the southern and southeastern regions (Topağaç, Gündoğdu,



**Figure 8.** NDVI difference analysis map of Marmara Island between 1991 and 2023

and Asmalı), suggesting localized vegetation recovery and the continued vitality of agricultural landscapes. Values exceeding +0.20 represent micro-scale areas of re-greening or vegetation regeneration. Overall, the findings highlight a spatial divergence in vegetation dynamics across Marmara Island during the 1991–2023 period. While persistent anthropogenic pressure has led to ecological degradation in the north, the southern parts demonstrate relative ecological resilience, supported by topographic protection and sustainable land-use practices.

The integrated NDVI and LULC analyses reveal that Marmara Island has undergone significant ecological and spatial transformations between 1991 and 2023, primarily driven by the expansion of marble quarrying activities. NDVI results indicate a continuous decline in vegetation density across the northern part of the island particularly around Saraylar, Çınarlı, and Asmalı where NDVI values have fallen from approximately 0.41 in 1991 to below 0.10 in 2023. The strong spatial correlation between low NDVI values and expanding marble extraction zones demonstrates the severe ecological footprint of prolonged quarrying operations. Conversely, the southern and southwestern parts of the island maintained relatively high NDVI values reflecting the persistence of agricultural forest mosaics that function as residual ecological buffers against further degradation. Stakeholder consultations support these spatial findings. Officials from the Balıkesir Metropolitan Municipality highlighted that the current legal framework allowing abandoned marble quarries to be re-leased to former operators for 49 years creates major obstacles to effective land restoration and ecological rehabilitation. The Balıkesir Chamber of Commerce emphasized that the visual and environmental degradation caused by extensive marble quarrying, confirmed by NDVI and LULC analyses, has undermined the island's tourism image and long-term investment potential. In addition, local residents expressed concerns about marble dust emissions, noise pollution, and declining agricultural productivity, particularly in olive groves situated adjacent to low-NDVI, high-disturbance zones.

Collectively, these findings underscore that the vegetation degradation detected through NDVI analyses and the spatial transformations identified by LULC modelling are deeply intertwined with governance and socio-economic dynamics. To address these interlinked challenges, an integrated spatial and policy framework involving policy makers, marble industry operators, ecological scientists, and the tourism sector is urgently needed. Such a collaborative approach is vital to reconcile economic productivity with ecological rehabilitation, strengthen participatory governance, and guide Marmara Island toward a more resilient and environmentally sustainable future.

#### 4. Discussion

The spatiotemporal patterns observed on Marmara Island between 1991 and 2055 clearly demonstrate that intensive marble quarrying has become the dominant driver

of landscape transformation. When integrated with NDVI-based ecological assessments, the LULC transitions reveal a coupled system of land degradation, vegetation decline, and fragmented rural economies. These findings align with previous research showing that extractive industries often trigger long-term ecological shifts, including habitat fragmentation, vegetation loss, and soil destabilisation in Mediterranean island ecosystems (Derdemezi et al., 2022; Boi et al., 2023). However, the magnitude of mining-driven change detected on Marmara Island exceeding a projected 122% increase in marble quarry area by 2055 surpasses the rates reported for many comparable island environments. This highlights the urgency of integrating ecological restoration and landscape planning into regional mining policies.

A meaningful parallel can be drawn with the Eden Project (Cornwall, UK), where a heavily degraded kaolinite mine was successfully transformed into a globally recognised ecological, educational, and tourism complex. Although the biophysical, economic, and policy contexts differ considerably, the Eden Project demonstrates that post-mining landscapes have the potential for ecological rehabilitation, socio-economic renewal, and cultural rebranding (Emir & Yıldırım, 2024). Similar examples can be found in other parts of the world. For instance, the Park am Gleisdreieck (Berlin, Germany) and the Landschaftspark Duisburg-Nord (Germany) illustrate how heavily industrial or mining-disturbed areas can be converted into multifunctional green infrastructures that support biodiversity while offering recreational and cultural services (Hemmings & Kagel, 2010; Ferrari, 2023). Collectively, these international examples underscore that post-mining restoration is scientifically feasible and socially beneficial when supported by robust governance frameworks and long-term investment.

Beyond ecological impacts, the long-term land-cover projections also carry important economic implications. Although reliable financial data could not be obtained due to institutional reluctance, a qualitative cost-benefit perspective illustrates stark contrasts between mining-based and nature-based development pathways. Mining provides short-term revenues and employment but generates substantial externalities landscape degradation, biodiversity loss, declining agricultural productivity, and reduced tourism potential (Giurco & Cooper, 2012; Zhang et al., 2023). Agriculture and olive cultivation, which historically shaped the island's socio-economic structure, are projected to decline by 32–64% by 2055, risking the loss of an important cultural and economic asset. Similarly, tourism a sector that relies on landscape quality and environmental aesthetics has already been negatively affected, as reported by local authorities and the Balıkesir Chamber of Commerce. When these indirect economic costs are considered, the long-term profitability of continuous mine quarry expansion becomes increasingly questionable. This aligns with valuations in comparable Mediterranean regions where diversified rural economies outperform mono-sector extractive economies in the long run (Haddaway et al., 2022; Wegenast & Beck, 2020).

A critical evaluation of the applied methods underscores the robustness and originality of this study. The integrated use of CA–Markov modelling and multi-temporal NDVI analysis effectively captures both the structural (land-use transitions) and functional (vegetation vitality) dimensions of landscape transformation. While previous research often examined these components separately, the combined approach adopted here offers a more holistic perspective on how anthropogenic pressures reshape physical land cover and ecological processes. The pixel-based LULC conversion map (1991–2055) quantifies the spatial expansion of mining activities and identifies limited zones with potential for ecological recovery. Furthermore, the strong spatial concordance between declining NDVI values and the enlarging marble quarry footprint reinforces the validity of the model outputs.

NDVI-based analysis provides valuable insights into the spatial and temporal variability of vegetation greenness and relative vegetation condition in response to land-use transitions. However, it is important to acknowledge that NDVI does not allow discrimination among vegetation species or community composition. Accordingly, the NDVI difference analysis between 1991 and 2023 should be interpreted as reflecting changes in overall vegetation condition, rather than transitions among specific vegetation types or species composition. This limitation does not undermine the validity of the results but instead defines the scale and interpretative framework within which NDVI-based findings remain robust and meaningful. Analysis of the NDVI difference indicates that the northern part of Marmara Island exhibits a pronounced negative trend associated with long-term marble quarrying activities, reflected in substantial vegetation decline and surface soil degradation, whereas relatively higher and more stable NDVI values are preserved in the southern and southwestern regions. This change exerts its most pronounced negative impacts on forested areas. In particular, in the Saraylar region where mining activities are most intensive on the island the expansion of quarrying areas clearly demonstrates the extent of damage inflicted on forest ecosystems. This spatial differentiation underscores the ecological pressure exerted by mining on vegetation cover and suggests that these impacts may be interpreted within a broader environmental context, including potential interactions with climate-related processes.

Overall, while this study has several strengths, there are also a number of limitations that should be taken into consideration. The CA–Markov model assumes that past transition trends will persist, potentially overlooking abrupt policy changes or economic shifts. The lack of detailed economic data particularly production costs, profit margins, and reclamation budgets constrains any comprehensive cost benefit evaluation. Moreover, NDVI alone cannot fully represent soil quality, biodiversity loss, or hydrological alterations. Future studies should therefore incorporate complementary ecological indicators such as habitat fragmentation metrics, soil erosion modelling, or water-quality assessments. Ground-truth data could also

enhance classification accuracy and ecological interpretation.

## 5. Conclusions

Marmara Island has an important place for Türkiye in ecological, economic, historical and cultural terms. Marmara Island has ecologically important values, especially with its natural vegetation, marine and coastal ecosystem. In addition, with its fishing activities, it contributes significantly to the economy of not only the people living on the island but also its immediate surroundings. In terms of history and culture, it has traces of settlement from ancient times and harbours many artefacts from different periods. The island, which has a rich cultural heritage, is also among the important tourism regions of Türkiye.

Marble quarrying, which dates back to antiquity, continues to serve as a major source of income for the island. However, the NDVI and LULC analyses conducted in this study reveal that the ongoing expansion of marble quarries has caused extensive ecological degradation. NDVI results indicate a consistent decline in vegetation density, particularly in the northern part of the island (Saraylar–Çınarlı–Asmalı), where NDVI values have dropped below 0.10, signifying severe vegetation loss and soil degradation. This spatial pattern corresponds with LULC findings, which show that mining areas expanded by 37.8% between 1991 and 2011, by 52% between 1991 and 2023, and are projected to increase by 122% by 2055. The continuous expansion of these areas has directly reduced shrubland, forest, grassland, and agricultural zones, resulting in a measurable decrease in NDVI values and overall ecological productivity.

The removal of natural vegetation during marble development has intensified erosion and landslide risks, disrupted local ecosystems, and contributed to biodiversity loss. At the same time, olive cultivation another key livelihood and cultural symbol of the island is under pressure. NDVI data indicate a decline in vegetation vigor within olive groves located near marble quarry sites, consistent with the projected reduction of olive areas by 15.4% between 1991–2023 and by 32.4% between 1991–2055. Dust emissions, blasting operations, and surface waste from marble processing not only reduce photosynthetic efficiency but also threaten groundwater and surface water quality.

Although the predicted 737 ha increase in marble quarry areas by 2055 may generate short-term economic benefits, it is expected to exacerbate ecological and socio-cultural damage in the long run. These findings emphasize that, in a world of limited natural resources and increasing human demand, maintaining a balance between conservation and utilization is essential. Integrating NDVI-based vegetation monitoring with predictive LULC modelling offers a powerful approach for understanding the temporal dynamics of land use, assessing the magnitude of anthropogenic impacts, and supporting sustainable landscape planning. Therefore, future management strategies for Marmara Island should prioritize ecosystem restoration,

controlled marble operations, and participatory planning that harmonizes economic productivity with ecological resilience and cultural continuity.

Although mining activities contribute substantially to the local and regional economy, their unregulated expansion has resulted in significant ecological degradation and socio-cultural disruption. Hence, there is an urgent need to adopt comprehensive mitigation strategies that reconcile economic development with environmental stewardship. In this regard, the following measures are recommended to ensure the sustainable management and long-term resilience of Marmara Island's landscape:

- Ecological restoration and reforestation: Immediate rehabilitation of abandoned and inactive mine quarry sites through native species to restore soil stability and biodiversity.
- Buffer zone creation: Establishment of vegetated buffer zones between mine quarry areas and agricultural or residential zones to reduce dust dispersion and noise impacts.
- Water and soil management: Implementation of sedimentation basins, terracing, and erosion-control vegetation to prevent runoff and protect groundwater quality.
- Monitoring and early-warning systems: Integration of NDVI-based vegetation monitoring and remote-sensing indicators into local land-use planning to continuously assess mine quarry impacts.
- Socio-economic diversification: Promotion of sustainable livelihoods such as eco-tourism, olive-based agriculture, and heritage tourism to reduce dependence on mine quarrying.
- Policy and governance improvements: Revision of legal frameworks that allow the re-leasing of abandoned quarries for 49 years, ensuring stricter environmental obligations and mandatory post-extraction restoration plans.

In conclusions, maintaining the ecological balance of Marmara Island requires an integrated management framework that harmonizes economic productivity with environmental sustainability. The combined use of NDVI and LULC analyses provides a scientifically robust foundation for adaptive land-use planning, guiding policymakers, local authorities, and stakeholders toward a more resilient and sustainable future for the island.

## Funding

This article has not been supported by any funding or financing.

## References

- Aksoy, R. (1999). Marmara Adası'nda ilerleyen bölgesel metamorfizma ile tektonik tarihçe arasındaki ilişki [The relationship between progressive regional metamorphism and structural history in the Marmara Island]. *Geological Bulletin of Turkey*, 42(1), 1–14.
- Altuner, F. (2022). *Alansal değişime etki eden parametrelerin Ayvalık ilçesi örneğinde incelenmesi* [The examination of parameters affecting the spatial change in the Ayvalık district example] [Doctoral dissertation, Çanakkale Onsekiz Mart University, School of Graduate Studies]. Canakkale.
- Alptekin, G. (2021). Marmara marble and current design examples in the context of sustainability. *Journal of Art & Design*, 9(4), 1–16.
- Amir Siddique, M., Wang, Y., Xu, N., Ullah, N., & Zeng, P. (2021). The spatiotemporal implications of urbanization for urban heat islands in Beijing: A predictive approach based on CA-Markov modeling (2004–2050). *Remote Sensing*, 13(22), Article 4697. <https://doi.org/10.3390/rs13224697>
- Anwer, H. A., Mohamed, T., & Hassan, A. (2025). Assessing vegetation dynamics in Al Jazirah, Sudan using NDVI-based remote sensing techniques. *Journal of the Saudi Society of Agricultural Sciences*, 24(4), 1–12. <https://doi.org/10.1007/s44447-025-00011-0>
- Appala, R. K., & Sivakumar, V. L. (2023). Hyderabad city land use/land cover changes multi-spatio temporal comparison using spectral angle mapper with maximum likelihood classification. *Journal of Survey in Fisheries Sciences*, 10(1S), 1748–1759.
- Atik, M., Altan, T., & Artar, M. (2010). Land use changes in relation to coastal tourism developments in Turkish mediterranean. *Polish Journal of Environmental Studies*, 19(1).
- Baqa, M. F., Chen, F., Lu, L., Qureshi, S., Tariq, A., Wang, S., Jing, L., Hamza, S., & Li, Q. (2021). Monitoring and modeling the patterns and trends of urban growth using urban sprawl matrix and CA-Markov model: A case study of Karachi, Pakistan. *Land*, 10(7), Article 700. <https://doi.org/10.3390/land10070700>
- Bazi, Y., Bashmal, L., Rahhal, M. M. A., Dayil, R. A., & Ajlan, N. A. (2021). Vision transformers for remote sensing image classification. *Remote Sensing*, 13(3), Article 516. <https://doi.org/10.3390/rs13030516>
- Behera, M., Borate, S. N., Panda, S. N., Behera, P. R., & Roy, P. S. (2012). Modelling and analyzing the watershed dynamics using Cellular Automata (CA)-Markov model – Ageo-information based approach. *Journal of Earth System Science*, 121(4), 1011–1024. <https://doi.org/10.1007/s12040-012-0207-5>
- Bhatti, M. T., Gilani, H., Ashraf, M., Iqbal, M. S., & Munir, S. (2024). Field validation of NDVI to identify crop phenological signatures. *Precision Agriculture*, 25(5), 2245–2270. <https://doi.org/10.1007/s11119-024-10165-6>
- Bingöl, F., Altuner, F., & Kelkit, A. (2023). Analyzing the most eligible site selection for biomass energy facilities through weighted overlay analysis: Case of Balıkesir (Türkiye) province. *Ege Üniversitesi Ziraat Fakültesi Dergisi*, 60(1), 19–35. <https://doi.org/10.20289/zfdergi.1136651>
- Boi, M. E., Fois, M., Podda, L., Porceddu, M., & Bacchetta, G. (2023). Using Mediterranean native plants for the phytoremediation of mining sites: An overview of the past and present, and perspectives for the future. *Plants*, 12(22), Article 3823. <https://doi.org/10.3390/plants12223823>
- Cai, M., Zhang, Y., Guan, X., & Qiu, J. (2025). An adaptive spatiotemporal tensor reconstruction method for GIMMS-3g+ NDVI. *Remote Sensing of Environment*, 316, Article 114511. <https://doi.org/10.1016/j.rse.2024.114511>
- Cao, M., Tian, Y., Wu, K., Chen, M., Chen, Y., Hu, X., Sun, Z., Zuo, L., Lin, J., Luo, L., Zhu, R., Xu, Z., Bandrova, T., Konecny, M., Yuan, W., Guo, H., Lin, H., & Lü, G. (2023). Future land-use change and its impact on terrestrial ecosystem carbon pool evolution along the Silk Road under SDG scenarios. *Science Bulletin*, 68(7), 740–749. <https://doi.org/10.1016/j.scib.2023.03.012>

- Cengiz, S., & Yılmaz, B. (2016, October 5–7). Modelling of land use/cover in Malatya, the simulation of 2025-2045 land use/cover. In *UZAL-CBS 2016 Symposium* (pp. 49–57). Adana.
- Chang, H., He, G., Wang, Q., Li, H., Zhai, J., Dong, Y., Zhao, Y., & Zhao, J. (2021). Use of sustainability index and cellular automata-Markov model to determine and predict long-term spatio-temporal variation of drought in China. *Journal of Hydrology*, 598, Article 126248. <https://doi.org/10.1016/j.jhydrol.2021.126248>
- Chen, L., Yan, G., Wang, T., Ren, H., Calbó, J., Zhao, J., & McKenzie, R. (2012). Estimation of surface shortwave radiation components under all sky conditions: Modeling and sensitivity analysis. *Remote Sensing of Environment*, 123, 457–469. <https://doi.org/10.1016/j.rse.2012.04.006>
- Cohen, J. (1968). Weighted kappa: Nominal scale agreement with provision for scaled disagreement or partial credit. *Psychological Bulletin*, 70(4), 213–220. <https://doi.org/10.1037/h0026256>
- Corry, R. C. (2005). Characterizing fine-scale patterns of alternative agricultural landscapes with landscape pattern indices. *Landscape Ecology*, 20, 591–608. <https://doi.org/10.1007/s10980-004-5036-8>
- Cui, Y., Li, L., Chen, L., Zhang, Y., Cheng, L., Zhou, X., & Yang, X. (2018). Land-use carbon emissions estimation for the Yangtze River delta urban agglomeration using 1994–2016 Landsat image data. *Remote Sensing*, 10, Article 1334. <https://doi.org/10.3390/rs10091334>
- Çetinkaya, B., & Toz, G. (2011). Coğrafi veri seçim işlemlerinin sonuçlarının değerlendirilmesinde hata matrisinin kullanımı. *İTÜ Dergisi/d*, 6(5–6).
- Daba, M. H., & You, S. (2022). Quantitatively assessing the future land-use/land-cover changes and their driving factors in the upper stream of the Awash River based on the CA-Markov model and their implications for water resources management. *Sustainability*, 14(3), Article 1538. <https://doi.org/10.3390/su14031538>
- Dale, V. H., & Kline, K. L. (2013). Issues in using landscape indicators to assess land changes. *Ecological Indicators*, 28, 91–99. <https://doi.org/10.1016/j.ecolind.2012.10.007>
- Derdemezi, E. T., Tsilimigkas, G., & Kizos, T. (2022). Mining activity and island landscape issues: Evidence from Cyclades islands, Greece. *European Planning Studies*, 30(2), 384–404. <https://doi.org/10.1080/09654313.2021.1958172>
- DeWitt, J. D., Chirico, P. G., Bergstresser, S. E., & Warner, T. A. (2017). Multi-scale 46-year remote sensing change detection of diamond mining and land cover in a conflict and post-conflict setting. *Remote Sensing Application Society Environment*, 8, 126–139. <https://doi.org/10.1016/j.rsase.2017.08.002>
- Dikgwatlhe, P., & Mulenga, F. (2023). Perceptions of local communities regarding the impacts of mining on employment and economic activities in South Africa. *Resources Policy*, 80, Article 103138. <https://doi.org/10.1016/j.resourpol.2022.103138>
- Ding, Y., Zhao, K., Zheng, X., & Jiang, T. (2014). Temporal dynamics of spatial heterogeneity over cropland quantified by time-series NDVI, near infrared and red reflectance of Landsat 8 OLI imagery. *International Journal of Applied Earth Observation and Geoinformation*, 30, 139–145. <https://doi.org/10.1016/j.jag.2014.01.009>
- Emir, H. N. S., & Yıldırım, E. (2024). Improving degraded landscapes and evaluating them as a learning environment “The Eden Project”. *Peyzaj*, 6(1), 15–30. <https://doi.org/10.53784/peyzaj.1495581>
- Esbah, H., Cook, E. A., & Ewan, J. (2009). Effects of increasing urbanization on the ecological integrity of open space preserves. *Environmental Management*, 43, 846–862. <https://doi.org/10.1007/s00267-009-9274-z>
- Farbo, A., Sarvia, F., De Petris, S., Basile, V., & Borgogno-Mondino, E. (2024). Forecasting corn NDVI through AI-based approaches using sentinel 2 image time series. *ISPRS Journal of Photogrammetry and Remote Sensing*, 211, 244–261. <https://doi.org/10.1016/j.isprsjprs.2024.04.011>
- Feng, Y., Liu, M., Liu, Y., Tong, X., & Deng, S. (2011). Modeling dynamic urban growth using cellular automata and particle swarm optimization rules. *Landscape and Urban Planning*, 102(3), Article 188–196. <https://doi.org/10.1016/j.landurbplan.2011.04.004>
- Ferrari, E. (2023). Along the western margin of Park Am Gleisdreieck, an urban hybrid environment. *Environment and History*, 29(4), 467–475. <https://doi.org/10.3197/096734023X16945097374236>
- Feyzolahpour, M. (2024). Analysis of changes in the surface of anzali wetland using spectral indices, random tree classification (RTC), and maximum likelihood classification (MLC) from 1992 to 2022. *Geographical Studies of Coastal Areas Journal*, 5(3), 18, 17–36.
- Footy, G. M. (2022). Global and local assessment of image classification quality on an overall and per-class basis without ground reference data. *Remote Sensing*, 14(21), Article 5380. <https://doi.org/10.3390/rs14215380>
- Fu, F., Deng, S., Wu, D., Liu, W., & Bai, Z. (2022). Research on the spatiotemporal evolution of land use landscape pattern in a county area based on CA-Markov model. *Sustainable Cities and Society*, 80, Article 103760. <https://doi.org/10.1016/j.scs.2022.103760>
- Ghosh, P., Mukhopadhyay, A., Chanda, A., Mondal, P., Akhand, A., Mukherjee, S., Nayak, S. K., Ghosh, S., Mitar, D., Ghosh T., & Hazra, S. (2017). Application of Cellular automata and Markov-chain model in geospatial environmental modeling- A review. *Remote Sensing Applications Society Environment*, 5, 64–77. <https://doi.org/10.1016/j.rsase.2017.01.005>
- Ghosh, S., Chatterjee, N. D., & Dinda, S. (2021). Urban ecological security assessment and forecasting using integrated DEM-ATEL-ANP and CA-Markov models: A case study on Kolkata Metropolitan Area, India. *Sustainable Cities and Society*, 68, Article 102773. <https://doi.org/10.1016/j.scs.2021.102773>
- Giurco, D., & Cooper, C. (2012). Mining and sustainability: Asking the right questions. *Minerals Engineering*, 29, 3–12. <https://doi.org/10.1016/j.mineng.2012.01.006>
- Gulpinar Sekban, D. U., & Acar, C. (2021). Determining usages in post-mining sites according to landscape design approaches. *Land Degradation & Development*, 32(8), 2661–2676. <https://doi.org/10.1002/ldr.3933>
- Haddaway, N. R., Smith, A., Taylor, J. J., Andrews, C., Cooke, S. J., Nilsson, A. E., & Lesser, P. (2022). Evidence of the impacts of metal mining and the effectiveness of mining mitigation measures on social-ecological systems in Arctic and boreal regions: A systematic map. *Environmental Evidence*, 11(1), Article 30. <https://doi.org/10.1186/s13750-022-00282-y>
- Han, J., Hayashi, Y., Gao, X., & Imura, H. (2009). Application of an integrated system dynamics and cellular automata model for urban growth assessment: A case study of Shanghai, China. *Landscape and Urban Planning*, 91(3), Article 133–141. <https://doi.org/10.1016/j.landurbplan.2008.12.002>
- He, Y., Qiu, H., Song, J., Zhao, Y., Zhang, L., Hu, S., & Hu, Y. (2019). Quantitative contribution of climate change and human activities to runoff changes in the Bahe River watershed of the Qinling Mountains, China. *Sustainable Cities and Society*, 51, Article 101729. <https://doi.org/10.1016/j.scs.2019.101729>
- Hemmings, S., & Kagel, M. (2010). Memory gardens: Aesthetic education and political emancipation in the “Landschaftspark Duisburg-Nord”. *German Studies Review*, 33(2), 243–261.

- Hou, H., Ding, Z., Zhang, S., Guo, S., Yang, Y., Chen, Z., Mi, J., & Wang, X. (2021). Spatial estimate of ecological and environmental damage in an underground coal mining area on the Loess Plateau: Implications for planning restoration interventions. *Journal of Cleaner Production*, 287, Article 125061. <https://doi.org/10.1016/j.jclepro.2020.125061>
- Hu, Y., Zheng, Y., & Zheng, X. (2013). Simulation of land-use scenarios for Beijing using CLUE-S and Markov composite models. *Chinese Geographical Science*, 23(1), 92–100. <https://doi.org/10.1007/s11769-013-0594-9>
- Hussain, S., Mubeen, M., Nasim, W., Mumtaz, F., Abdo, H. G., Mostafazadeh, R., & Fahad, S. (2024). Assessment of future prediction of urban growth and climate change in district Multan, Pakistan using CA-Markov method. *Urban Climate*, 53, Article 101766. <https://doi.org/10.1016/j.uclim.2023.101766>
- Hyandye, C., & Martz, L. W. (2017). A Markovian and cellular automata land-use change predictive model of the Usangu Catchment. *International Journal of Remote Sensing*, 38(1), 64–81. <https://doi.org/10.1080/01431161.2016.1259675>
- Istanbul Mineral Exporters Association. (2024). *Mineral export index reports*. <https://imib.org.tr/en/>
- Kalaycı, M., & Uzun, O. (2017). Recreational purpose evaluation of mine areas after mining. *Uluslararası Bilimsel Araştırmalar Dergisi (IBAD)*, 2(2), 232–244. <https://doi.org/10.21733/ibad.2131>
- Kariuki, R. W., Capitani, C., Munishi, L. K., Shoemaker, A., Courtney Mustaphi, C. J., William, N., Jane, P., & Marchant, R. (2022). Serengeti's futures: Exploring land use and land cover change scenarios to craft pathways for meeting conservation and development goals. *Frontiers in Conservation Science*, 3, Article 920143. <https://doi.org/10.3389/fcosc.2022.920143>
- Karlis, D. (2002). An EM type algorithm for maximum likelihood estimation of the normal-inverse Gaussian distribution. *Statistics & Probability Letters*, 57(1), 43–52. [https://doi.org/10.1016/S0167-7152\(02\)00040-8](https://doi.org/10.1016/S0167-7152(02)00040-8)
- Keenan, J., & Holcombe, S. (2021). Mining as a temporary land use: A global stocktake of post-mining transitions and repurposing. *The Extractive Industries and Society*, 8(3), Article 100924. <https://doi.org/10.1016/j.exis.2021.100924>
- Keshtkar, H., & Voigt, W. (2016). A spatiotemporal analysis of landscape change using an integrated Markov chain and cellular automata models. *Modeling Earth Systems and Environment*, 2(1), Article 10. <https://doi.org/10.1007/s40808-015-0068-4>
- Khunrattanasiri, W. (2020). Comparative study on CA-Markov model and CLUE-S model for land use changed prediction in National Reserved Forest, Nan province. *The Journal of Applied Science*, 19, 87–100. <https://doi.org/10.14416/j.appsci.2020.02.008>
- Khwarahm, N. R., Qader, S., Ararat, K., & Fadhil Al-Quraishi, A. M. (2021). Predicting and mapping land cover/land use changes in Erbil/Iraq using CA-Markov synergy model. *Earth Science Informatics*, 14(1), 393–406. <https://doi.org/10.1007/s12145-020-00541-x>
- Koç, D. E., & Gündüz, Z. (2022). Relationship between geomorphological units with land use in the Marmara Island. *Sosyal, Beşerî ve İdari Bilimler Dergisi*, 5(9), 1279–1292.
- Köse, M., & Kul, A. A. (2020). Investigation of sustainable utilization from wetlands and their surroundings in abandoned mining sites: Istanbul case study. *Turkish Journal of Forestry*, 21(3), 243–253. <https://doi.org/10.18182/tjf.710561>
- Kriegler, F. J., Malila, W. A., Nalepka, R. F., & Richardson, W. (1969). Preprocessing transformations and their effect on multispectral recognition. *Remote Sensing Environment*, 1, 97–132.
- Kumar, A., & Garg, R. D. (2023). Land cover mapping and change analysis using optimized random forest classifier incorporating fusion of texture and Gabor features. *SN Computer Science*, 4(5), Article 685. <https://doi.org/10.1007/s42979-023-02111-6>
- Kumar, A., & Sharma, S. K. (2022). Information cryptography using cellular automata and digital image processing. *Journal of Discrete Mathematical Sciences and Cryptography*, 25(4), 1105–1111. <https://doi.org/10.1080/09720529.2022.2072437>
- Lemenkova, P., & Debeir, O. (2023). Computing vegetation indices from the satellite images using GRASS GIS scripts for monitoring mangrove forests in the coastal landscapes of Niger Delta, Nigeria. *Journal of Marine Science and Engineering*, 11(4), Article 871. <https://doi.org/10.3390/jmse11040871>
- Li, X., Xu, J., Jia, Y., Liu, S., Jiang, Y., Yuan, Z., Du, H., Han, R., & Ye, Y. (2024). Spatio-temporal dynamics of vegetation over cloudy areas in Southwest China retrieved from four NDVI products. *Ecological Informatics*, 81, Article 102630. <https://doi.org/10.1016/j.ecoinf.2024.102630>
- Listyono, G. M., & Manurung, P. (2025). Land use and land cover (LULC) change from 2010 to 2015 driven by mining industries: A case study in Obi Island, Indonesia. *Journal of Degraded and Mining Lands Management*, 12(5), 8677–8691. <https://doi.org/10.15243/jdmlm.2025.125.8677>
- Mansour, S., Al-Belushi, M., & Al-Awadhi, T. (2020). Monitoring land use and land cover changes in the mountainous cities of Oman using GIS and CA-Markov modelling techniques. *Land Use Policy*, 91, Article 104414. <https://doi.org/10.1016/j.landusepol.2019.104414>
- Markov, A. A. (1906). Extension of the law of large numbers to dependent quantities. *Journal Électronique d'Histoire des Probabilités et de la Statistique*, 15(1), 135–156. <http://eudml.org/doc/128778>
- McGarigal, K., Compton, B. W., Plunkett, E. B., DeLuca, W. V., Grand, J., Ene, E., & Jackson, S. D. (2018). A landscape index of ecological integrity to inform landscape conservation. *Landscape Ecology*, 33, 1029–1048. <https://doi.org/10.1007/s10980-018-0653-9>
- Mhlongo, S. E. (2023). Evaluating the post-mining land uses of former mine sites for sustainable purposes in South Africa. *Journal of Sustainable Mining*, 22(2), Article 3. <https://doi.org/10.46873/2300-3960.1381>
- Mi, J., Yang, Y., Zhang, S., An, S., Hou, H., Hua, Y., & Chen, F. (2019). Tracking the land use/land cover change in an area with underground mining and reforestation via continuous Landsat classification. *Remote Sensing*, 11(14), Article 1719. <https://doi.org/10.3390/rs11141719>
- Mohan, M., Pathan, S.K., Narendrareddy, K., Kandya, A., & Pandey, S. (2011). Dynamics of urbanization and its impact on land-use/land-cover: A case study of megacity Delhi. *Journal of Environmental Protection*, 2(9), 1274–1283. <https://doi.org/10.4236/jep.2011.29147>
- Myint, S. W., & Wang, L. (2006). Multicriteria decision approach for land use land cover change using Markov chain analysis and a cellular automata approach. *Canadian Journal of Remote Sensing*, 32(6), 390–404. <https://doi.org/10.5589/m06-032>
- Ngandam Mfondoum, A. H., Hakdaoui, S., & Batcha, R. (2022). Landsat 8Bands'1 to 7 spectral vectors plus machine learning to improve land use/cover classification using Google Earth Engine. *Annals of GIS*, 28(3), 401–424. <https://doi.org/10.1080/19475683.2022.2026475>
- Olufayokemi Rasheedat, O., & Ojodale Samuel, U. (2025). Geospatial analysis of vegetation health response to urbanisation and land use/land cover changes in Lokoja, Nigeria using NDVI. *Integral Research*, 2(4), 49–72.
- Punia, A., Joshi, P. K., & Siddaiah, N. S. (2021). Characterizing Khetri copper mine environment using geospatial tools. *SN*

- Applied Sciences*, 3(2), Article 174.  
<https://doi.org/10.1007/s42452-021-04183-6>
- Rau, G., & Shih, Y. S. (2021). Evaluation of Cohen's kappa and other measures of inter-rater agreement for genre analysis and other nominal data. *Journal of English for Academic Purposes*, 53, Article 101026. <https://doi.org/10.1016/j.jeap.2021.101026>
- Rentier, E. S., & Cammeraat, L. H. (2022). The environmental impacts of river sand mining. *Science of the Total Environment*, 838, Article 155877.  
<https://doi.org/10.1016/j.scitotenv.2022.155877>
- Rimal, B., Zhang, L., Keshtkar, H., Haack, B., Rijal, S., & Zhang, P. (2018). Land use/land cover dynamics and modeling of urban land expansion by the integration of cellular automata and Markov chain. *ISPRS International Journal of Geo-Information*, 7(4), Article 154. <https://doi.org/10.3390/ijgi7040154>
- Rouse, J. W. (1973). Monitoring vegetation systems in the great plains with ERTS. In *Third NASA Earth Resources Technology Satellite Symposium* (pp. 309–317). <https://cir.nii.ac.jp/crid/1571417124296079488# CitationsContainer>
- Running, S. W. (1990). Estimating terrestrial primary productivity by combining remote sensing and ecosystem simulation. In R. J. Hobbs & H. A. Mooney (Eds.), *Remote sensing of biosphere functioning* (pp. 65–86). Springer-Verlag.  
[https://doi.org/10.1007/978-1-4612-3302-2\\_4](https://doi.org/10.1007/978-1-4612-3302-2_4)
- Sahu, P., & Kumawat, D. M. (2022). Spatial analysis of Biomass Cover status around an Iron ore mine in the Kalimati forest area of the Joda mining circle of Keonjhar district by using the NDVI application. *Journal of Geointerface*, 1(2), 44–50.
- Sakizadeh, M., Milewski, A., & Taghi Sattari, M. (2023). Analysis of long-term trend of stream flow and interaction effect of land use and landcover on water yield by SWAT model and statistical learning in part of Urmia Lake Basin, Northwest of Iran. *Water*, 15(4), 1–25. <https://doi.org/10.3390/w15040690>
- Sang, L., Chao, Z., Yang, J., Zhu, D., & Yun, W. (2011). Simulation of land use spatial pattern of towns and villages based on CA-Markov model. *Mathematical Computer Modelling*, 54(3–4), 938–943. <https://doi.org/10.1016/j.mcm.2010.11.019>
- Sarwar, A., Mehmood, Z., Saba, T., Qazi, K. A., Adnan, A., & Jamal, H. (2019). A novel method for content-based image retrieval to improve the effectiveness of the bag-of-words model using a support vector machine. *Journal of Information Science*, 45(1), 117–135. <https://doi.org/10.1177/0165551518782825>
- Seto, K. C., Güneralp, B., & Hutya, L. R. (2012). Global forecasts of urban ex-pansion to 2030 and direct impacts on biodiversity and carbon pools. *Proceedings of the National Academy of Sciences*, 109(40), 16083–16088.  
<https://doi.org/10.1073/pnas.1211658109>
- Sharma, L. K., Bu, H., Denton, A., & Franzen, D. W. (2015). Active-optical sensors using red NDVI compared to red edge NDVI for prediction of corn grain yield in North Dakota, USA. *Sensors*, 15(11), 27832–27853. <https://doi.org/10.3390/s151127832>
- Shivakumar, B. R., & Rajashekararadhya, S. V. (2018). Investigation on land cover mapping capability of maximum likelihood classifier: A case study on North Canara, India. *Procedia Computer Science*, 143, 579–586.  
<https://doi.org/10.1016/j.procs.2018.10.434>
- Solaimani, K., & Darvishi, S. (2024). Comparative analysis of land use changes modeling based-on new hybrid models and CA-Markov in the Urmia lake basin. *Advances in Space Research*, 74(8), 3749–3764. <https://doi.org/10.1016/j.asr.2024.06.078>
- Soltanmohammadi, H., Osanloo, M., & Bazzazi, A. A. (2010). An analytical approach with a reliable logic and a ranking policy for post-mining land-use determination. *Land Use Policy*, 27, 364–372. <https://doi.org/10.1016/j.landusepol.2009.05.001>
- Subedi, P., Subedi, K., & Thapa, B. (2013). Application of a hybrid cellular automaton–Markov (CA-Markov) model in land-use change prediction: A case study of Saddle Creek Drainage Basin, Florida. *Applied Ecology and Environmental Sciences*, 1(6), 126–132. <https://doi.org/10.12691/aees-1-6-5>
- Thakur, S., Maity, D., Mondal, I., Basumatary, G., Ghosh, P. B., Das, P., & De, T. K. (2021). Assessment of changes in land use, land cover, and land surface temperature in the mangrove forest of Sundarbans, northeast coast of India. *Environment, Development and Sustainability*, 23, 1917–1943.  
<https://doi.org/10.1007/s10668-020-00656-7>
- Theres, B. L., & Selvakumar, R. (2022). Comparison of landuse/landcover classifier for monitoring urban dynamics using spatially enhanced landsat dataset. *Environmental Earth Sciences*, 81(5), Article 142. <https://doi.org/10.1007/s12665-022-10242-x>
- Tobler, W. R. (1970). A computer movie simulating urban growth in the Detroit region. *Economic Geography*, 46, 234–240.  
<https://doi.org/10.2307/143141>
- Ulam, S. (1962). On some mathematical problems connected with patterns of growth of figures. In *Proceedings of Symposia in Applied Mathematics* (pp. 215–224). American Mathematical Society. <https://doi.org/10.1090/psapm/014/9947>
- Uzun, M. (2023). Analysis of changes caused by marble quarries in Marmara Island with anthropogenic geomorphology approach. *Eastern Geographical Review*, 28(50), 75–87.  
<https://doi.org/10.5152/EGJ.2023.23071>
- Uzun, O., & Bollukcu, P. (2009). Assessment of surface mining areas in Bartın central county in terms of biological landscape reclamation. In *Bartın Orman Fakültesi Dergisi I. Ulusal Batı Karadeniz Ormanlık Kongresi Bildiriler Kitabı, Özel Sayı* (pp. 486–500). [https://www.researchgate.net/publication/316879816\\_BARTIN\\_MERKEZ\\_ILCE\\_SINIRLARI\\_ICINDE\\_YER\\_ALAN\\_ACIK\\_OCAK\\_ISLETMELERININ\\_PEYZAJ\\_ONARIMI\\_-\\_BIYOLOJIK\\_ONARIM\\_ACISINDAN\\_DEGERLENDIRILMESI](https://www.researchgate.net/publication/316879816_BARTIN_MERKEZ_ILCE_SINIRLARI_ICINDE_YER_ALAN_ACIK_OCAK_ISLETMELERININ_PEYZAJ_ONARIMI_-_BIYOLOJIK_ONARIM_ACISINDAN_DEGERLENDIRILMESI)
- Verburg, P. H., & Overmars, K. P. (2009). Combining top-down and bottom-up dynamics in land use modeling: Exploring the future of abandoned farmlands in Europe with the Dyna-CLUE model. *Landscape Ecology*, 24(9), 1167–1181.  
<https://doi.org/10.1007/s10980-009-9355-7>
- Vergni, L., Todisco, F., & Di Lena, B. (2021). Evaluation of the similarity between drought indices by correlation analysis and Cohen's Kappa test in a Mediterranean area. *Natural Hazards*, 108(2), 2187–2209.  
<https://doi.org/10.1007/s11069-021-04775-w>
- Visser, H., & de Nijs, T. (2006). The map comparison kit. *Environmental Modelling & Software*, 21, 346–358.  
<https://doi.org/10.1016/j.envsoft.2004.11.013>
- Vohra, R., & Tiwari, K. C. (2023). Analysis of land use and land cover changes and their impact on temperature using landsat satellite imageries. *Environment, Development and Sustainability*, 25(8), 8623–8650.  
<https://doi.org/10.1007/s10668-022-02416-1>
- von Neumann, J. (1966). *Theory of self-reproducing automata* (A. W. Burks, Ed.). University of Illinois Press.
- Wegenast, T., & Beck, J. (2020). Mining, rural livelihoods and food security: A disaggregated analysis of sub-Saharan Africa. *World Development*, 130, Article 104921.  
<https://doi.org/10.1016/j.worlddev.2020.104921>
- Xu, D., Zhang, K., Cao, L., Guan, X., & Zhang, H. (2022). Driving forces and prediction of urban land use change based on the geodetector and CA-Markov model: A case study of Zhengzhou, China. *International Journal of Digital Earth*, 15(1), 2246–2267. <https://doi.org/10.1080/17538947.2022.2147229>

- Xue, H., Shen, X., & Pan, W. (2021). Constrained maximum likelihood-based Mendelian randomization robust to both correlated and uncorrelated pleiotropic effects. *The American Journal of Human Genetics*, 108(7), 1251–1269. <https://doi.org/10.1016/j.ajhg.2021.05.014>
- Yang, X., Zheng, X.-Q., & Lv, L.-N. (2012). A spatiotemporal model of land use change based on ant colony optimization, Markov chain and cellular automata. *Ecological Modelling*, 233, 11–19. <https://doi.org/10.1016/j.ecolmodel.2012.03.011>
- Zhang, J., Zhang, J., Wu, C., Zhang, Y., Guo, M., Li, H., & Wang, R. (2023). Comprehensive quantitative evaluation of the future mining: A comparison of socio-economic benefits and eco-environmental impacts. *Ore Geology Reviews*, 162, Article 105727. <https://doi.org/10.1016/j.oregeorev.2023.105727>
- Zheng, F., & Hu, Y. (2018). Assessing temporal-spatial land use simulation effects with CLUE-S and Markov-CA models in Beijing. *Environmental Science and Pollution Research*, 25(32), 32231–32245. <https://doi.org/10.1007/s11356-018-3189-2>
- Zhou, W., Wang, J., Qian, Y., Pickett, S. T., Li, W., & Han, L. (2018). The rapid but “invisible” changes in urban greenspace: A comparative study of nine Chinese cities. *Science of the Total Environment*, 627, 1572–1584. <https://doi.org/10.1016/j.scitotenv.2018.01.335>